Available online at www.sciencedirect.com
ScienceDirect
Technological Forecasting & Social Change 74 (2007) 682–707
Technological Forecasting and Social Change

Trends in energy consumption and carbon dioxide emissions of passenger cars and buses

J.A. Paravantis *, D.A. Georgakellos

University of Piraeus, Piraeus, 18534 Greece

Received 24 September 2005; received in revised form 13 March 2006; accepted 1 May 2006

Abstract

In this work we develop aggregate car ownership and bus fleet models in order to forecast and compare fuel consumption and CO_2 emissions from passenger cars and buses. Greece was selected as a case study, being a country fairly representative of lower-income Mediterranean and Eastern European countries and data were collected for the period 1970 to 2002. Percent adults in the population, per capita gross domestic product, inflation, unemployment, car occupancy and bus kilometers were predictors included in the car ownership and bus fleet multiple regression models. A shift in the overall trend of both models around 1995 was explained as a slope change of per capita gross domestic product, possibly reflecting the impact of a boom of the Greek Stock Market along with a retirement program for older vehicles. Predictor variables were forecast via Box–Jenkins and the models were subsequently used to develop car ownership and bus fleet forecasts to the year 2010. We predict that the contribution of cars to total CO_2 emissions will rise to an astounding 95% of total CO_2 emissions from road passenger transport (excluding taxis and mopeds), an effect expected in other Mediterranean and Eastern European countries with socioeconomic characteristics similar to Greece. Suggestions for further research include developing regional car ownership forecasts in order to compare the dynamics of different regions within a country and looking into other land transportation means (such as mopeds, taxicabs and railway).

Keywords: Carbon dioxide emissions; Energy consumption; Car ownership

* Corresponding author. 80 Karaoli and Dimitriou, University of Piraeus, Piraeus, 18534 Greece. Tel.: +30 2104142771; fax: +30 2104142753.

E-mail address: jparav@unipi.gr (J.A. Paravantis).

0040-1625/$ - see front matter © 2006 Elsevier Inc. All rights reserved.
doi:10.1016/j.techfore.2006.05.005

1. Introduction

In 1999, the transport sector was responsible for 21% of total energy use [1] and has become the fastest growing energy consuming sector worldwide [2]. Within the European Union (EU), transport is responsible for about 34% of total energy consumption with an annual growth of about 3% (1998 data; [3]). The main cause of this increase in energy use up to 1997 was growth in road transport [4]. During recent decades there has been a dramatic shift towards road transport: between 1970 and 1997, the car increased its share of passenger transport from 65% to 74%; trucks now account for 45% of total freight transport, compared to 30% in 1970. Between 1970 and 1997, passenger and freight transport in the EU increased by an annual average of 2.8 and 2.6% respectively; Gross Domestic Product (GDP) growth over the same period was 2.5%. For road and air-passenger travel in particular, the boost in demand may be attributed to higher income motivating people to switch to faster means, a fall in transport prices in real terms and changes in travel patterns (in part caused by urban sprawl). In turn, the demand and intensity (ton–km transported per unit of economic activity) of freight transport is closely linked to changes in the volume and structure of the economy as well as supply of infrastructure [5].

Contrary to what happened in the USA, in Europe (and Japan) the private car diffused much later and large-scale urbanization did not occur [6]; this was mainly due to higher population densities, higher land prices and subsidies to maintain or improve mass transport systems (including mass transit buses). While motorized mobility has grown spectacularly in many countries, public mass transportation modes such as buses and railways retain a stronger role in Central and Eastern Europe as well as in some Mediterranean countries such as Greece, Portugal and Spain. Looking at the modal split of passenger road transport among private cars and buses, EU data show that buses and coaches represent a varying 4.3 to 22.8% of total passenger kilometers (pkm) among member countries [7]; interestingly, this percentage tends to be lower in the case of richer countries such as the Netherlands (4.3), France (4.7), Great Britain (6.3) and Germany (8.9) and higher in the case of poorer countries such as Greece (19.9), the Slovak Republic (22.8), Latvia (24) and Hungary (24.3).

As living standards in these countries rise and more people switch to passenger cars, we expect bus usage to decrease further so that modal split approaches that of richer countries. This, in turn, will have repercussions on both fuel consumption and carbon dioxide (CO_2) emissions from road transport. Selecting Greece as the target population (being a country fairly representative of Southern Europe as well as Eastern European countries that were recently accepted into the EU), in this work we develop aggregate car ownership and bus fleet models in order to forecast fuel consumption and CO_2 emissions from passenger cars and buses with the objective of quantifying the contribution of each transport means to total CO_2 emissions in road passenger transport.

2. Background

Transport is the main area for growth in energy-related greenhouse gas (GHG) emissions, having increased by 19.5% across the EU between 1990 and 1999, reflecting growing demand for passenger and freight transport. In 1997, road energy consumption was 74.2% of the total for the transport sector [1] while, in 1998, road transport accounted for 84% of emissions [8]; these emissions are projected to increase by 15% until 2015 and 30% until 2030 [1]. Whereas road transport emissions of nitrogen oxides (NO_x), non-methane volatile organic compounds (NMVOC) and particulate matter (PM) have been reduced as a result of exhaust gas treatment and improved combustion technology, CO_2 emissions continue to increase [9] and now constitute the bulk of overall transport emissions (97%).

CO_2 emissions from the transport sector increased by 15% (from 700 to 800 million tones) between 1990 and 1998. This increase was caused by increases in road and air transport that were the fastest growing contributors to transport CO_2 emissions between 1990 and 2001 [10]. This upward trend in CO_2 emissions from transport is due mainly to growing traffic volumes [11]. The largest contributor to transport CO_2 emissions is road transport (84% of emissions in 1998); in 1990, the share of road transport in total CO_2 emissions was 18%, which increased to 20% by 1998.

CO_2 emissions from transport are equal to the product of transport activity (measured in passenger kilometers or tone kilometers), modal split (the share of each activity by transport mode), modal energy intensity (energy use per unit of passenger or freight travel by mode), and emission rate (CO_2 emissions per unit of energy consumed). CO_2 emissions from automobiles are related to fuel consumption. Car manufacturers often suggest that fuel consumption per kilometer (known as specific fuel consumption) of new car models is continually decreasing. However, Scholl, Schipper and Kiang [12] report on a rather bleak picture on fuel economy numbers that have stagnated particularly in the USA. Data from some Western European countries (such as Sweden and Italy) show that specific fuel consumption of the car fleet has not decreased in the last few years, while in other countries (such as the United Kingdom and Denmark) the decline continues albeit at a much lower pace than that up to the late eighties; also, specific fuel consumption of the car fleet in the Netherlands did not decline at all between 1990 and 1997 [13]. An explanation of this lies in the increasing use of heavier, more powerful cars and trucks, together with low occupancy rates and load factors that have offset improvements in fuel economy (mostly related to engine technology). Projections to 2010 show that energy consumption by transport is expected to follow growth in transport demand, even though significant reductions in fuel consumption by new cars and trucks are likely to be realized [4]. All in all, transportation is projected to consume 55% of all petroleum usage by 2020 [1].

Given the significance of the transport sector as a consumer of energy and producer of greenhouse gas emissions, there exists a large number of pertinent research studies that focus on various technological and non-technological issues [14]. Some of these studies propose methodologies and models for calculating energy consumption and/or air pollutant emissions from transport [15–20]; several studies go further and investigate the external cost of transport [21–24] while others study the influence of various driving patterns (such as speed) on fuel use and exhaust emission issues in road transport [25,26].

Comparative studies of transport modes based on environmental criteria mainly focus on energy use and the emission of air pollutants associated with the use of vehicles. In a survey of passenger transport in nine OECD countries (USA, Japan, France, former West Germany, Italy, UK and Denmark) over the period 1973–1992, Scholl, Schipper and Kiang [12] examined population growth, activities, mode shifts, fuel choices, fuel efficiency and the loading factor (i.e. car occupancy). The authors found that increased travel activity (mostly in passenger cars) and modal shifts boosted energy consumption and CO_2 emissions from travel almost everywhere; per capita emissions increased in Europe but declined in the USA and, interestingly, low per capita emitters had the greatest growth in per capita emissions over the period examined. The authors further discussed how changes in the fuel mix, lower transport intensities and reduced travel levels may stop the increase (or even reduce) CO_2 emission from transport. Finally the authors predicted continued increase in transport and transport emissions particularly in the case of cars and airplanes, noting that, in constant terms, the price of gasoline and other transport fuels had fallen to near their 1973 levels while energy intensities remained the same of were falling very slowly.

Schipper et al. regarded increasing passenger kilometers per capita and a shift towards the private car to be the main factors driving up energy use in most countries [27]. In a study carried out in the Netherlands, characteristics like energy use, travel time and use of space of each land transport mode were estimated, based on average distance traveled [28] whereas the analysis of these characteristics was carried out by studying the complete life-cycle energy use of each transportation system. Specific energy use was estimated at 1.79 MJ/pkm for gasoline passenger cars, 1.42 MJ/pkm for diesel passenger cars and 1.44 MJ/pkm for liquefied natural gas (LNG) passenger cars; in comparison, the average energy efficiency of the car fleet in EU has been reported as 1.64 MJ/pkm [29]. Correspondingly, average EU values of specific emissions of air pollutants (including volatile organic compounds, particulate matter, NO_x and CO) are about 5.2 g/pkm for cars and 1.1 g/pkm for buses [30]; in comparison, the specific emission rate of CO_2 is 189.3 g/pkm [29].

Apart from projects and reports providing measurements and similar information concerning vehicular emissions and energy efficiency factors [31–34], a number of case studies have been published that relate to the impact of road transport on fuel consumption and (more often) on air pollutants emissions (mainly based on atmospheric dispersion models or life cycle assessment) concerning regions in Sweden [35,36], Britain [37], the Netherlands [13,28], Central and Eastern Europe countries [2] and Greece [38–43]. Finally, some studies examine mitigation options [44–47] and the impact of green taxes and other incentives [48–50].

While it becomes fairly obvious that fuel consumption in the road transport sector and the resulting GHG emissions have been well investigated, little effort has been invested in discriminating among passenger cars and buses. In order to forecast CO_2 emissions from passenger cars on a national or regional level, an aggregate car ownership model may be used with an estimate of car mileage (there exist scanty records of annual mileage in the case of private automobiles). Similarly, a bus fleet model along with bus mileage information may be used to forecast CO_2 emissions from buses. Part of the problem is that although a significant amount of literature on car ownership models does exist (some reviewed later in this paper), there are (to our knowledge) no published works on bus fleet modeling.

3. Methodology

Given the goal of this work, our research is carried out in the following steps:

A. In step one, we develop aggregate models based on historical data for (a) passenger cars and (b) buses:
   1. Based on (car ownership and bus fleet) literature findings, we propose functional forms of (a) car ownership and (b) bus fleet models, considering for inclusion a small number of strong independent variables.
   2. We then describe available time series data and graph historical trends for dependent and independent variables for the case of Greece, that was selected as an appropriate target for our work.
   3. Finally, we estimate alternative formulations of the proposed regression models with either Ordinary Least Squares (OLS) or Generalized Least Squares (GLS) as appropriate and select the best car and bus model based on a priori expectations and statistical performance.

B. In step two, we use the best car ownership and bus fleet models to forecast the number of private cars and size of bus fleet until the year 2010:
   1. At first, we use Box-Jenkins techniques (ARIMA) to get forecasts for the independent variables employed in the best models.
   2. Subsequently, we plug independent variable forecasts into the best car ownership and bus fleet models in order to calculate forecasts for the dependent variables.
C. In step three, based on the previous forecasts, we calculate fuel consumption and estimate CO_2 emissions from private cars and buses and compare the resulting trends.

Minitab version 14.20 and Gretl version 1.5.0 [51] were used for graphing and statistical analysis.

4. Model specification

4.1. Passenger cars

Scholl, Schipper and Kiang [12] discuss how the demand for passenger transport is affected by lifestyles, income, fuel prices, labor structure, travel time and cost as well as urban development and point out that population growth magnifies the impact of these effects. Developing an aggregate model of car ownership in Asian countries, Prevedouros and An [52] identified population, income and unemployment rate as important car ownership factors and warned that income, car prices and fuel prices usually present multicollinearity problems; their model included GDP lagged by 1 year, a Consumer Price Index deflator, the unemployment rate, railway mileage and railway passenger mileage. Lam and Tam [53] chose population, population density, annual gross domestic product, first registration tax, annual license fee, gasoline price, annual passenger trips on public transport and annual railway passenger kilometers in order to estimate an aggregate car ownership model for Hong Kong.

Cars and population are strongly related although population is also likely to be correlated to economic measures such as Gross Domestic Product (GDP). Therefore, to avoid collinearity problems, the car ownership ratio (e.g. number of cars per 100 persons) is often utilized as a better choice of a dependent variable. A related population metric of interest, the adults ratio, has been shown by Gately [54] to be important in explaining the rapid growth in the number of drivers from the mid 1960s to the mid 1970s.

Dargay and Gately [55] developed a model expressing the growth of car ownership as a function of per capita income and discussed a number of additional independent variables that may influence vehicle ownership such as population density. Unfortunately, estimating true population density reliably is not trivial: total land area includes uninhabited parts while urban conurbations are sources of great inhomogeneity; to this effect, the percentage of urban population may be another independent variable worthy of investigation. An Irish study discussed below [56] observed that car ownership is rather low in Dublin, despite the fact that incomes per adult were typically 20% above that for other countries and suggested that car ownership tends to be highest in low-density countries with above average incomes where (as is the case in Dublin) there exists a higher level of public transport provision. Dargay and Gately concluded that no density measure appears to be very useful in explaining car ownership (including the logarithm of cars per population). This must definitely be the case with Greece, a mountainous country of great inhomogeneity with a large insular component, therefore we choose to ignore population density effects in this work.

The aforementioned Irish study on transport demand [56] suggested that there is a close correlation between car ownership and economic growth; for example, car ownership in Ireland stagnated in the early 1980s when the economy was performing poorly but has grown rapidly in recent years in line with the exceptional performance of the economy. Since income is a major indicator of economic growth, income levels are a major influence on car ownership; UK sources corroborate this thesis by supporting a correlation between gross annual household income and availability of one or more cars to that household [57]. Scholl, Schipper and Kiang [12] reported that most sources consider higher income as the driving force behind the increase in both car ownership and car use which in turn affect CO_2 emission increases; on the other hand, they argue that higher car ownership leads to a decline in the relative importance of bus and local/intercity train travel. Button, Fowkes and Pearman [58] discussed various aspects of the relationship between car ownership and income and explained how it leads to a sigmoid curve, testing (among others) a logistic, a quadratic and a Gompertz formulation for extrapolation of UK car ownership level data. Baldwin, Hess and Ong [59] point out that existing literature indicates that increasing income raises the amount that households spend on transportation, which is reflected in auto ownership. The relationship between income and car ownership is likely to be nonlinear because car ownership grows with income level but the impact of income declines as a certain saturation level is approached: the logistic, the quadratic and the Gompertz function have been employed to model this effect [58,60,55]. In response to these studies, in this work we looked into GDP, public and private Domestic Demand (DD) consumption and investments in order to choose the most appropriate measure of per capita income. We also decided to compare the performance of these level measures to that of their log-transformed form in order to determine how to best represent the declining effect of income (without resorting to a nonlinear logistic function and having to assume arbitrary values for vehicle saturation). We found that, in our data set, GDP per capita correlated best with cars per 100 people and was chosen as our preferred surrogate representation of per capita income.

On the cost side, Dargay and Gately [55] examined fixed (e.g. insurance, road tax, vehicle licensing fees and garaging fees) and variable (e.g. fuel costs, maintenance and repairs, oil, parking fees, tolls) vehicle costs. Contrary to Hong Kong where first registration tax and first license fee are high in an effort to control the number of private cars [53], in Greece they are quite low and do not operate as disincentives in owning a car; car prices on the other hand, include heavy taxation and may influence the decision to own a car but they are collinear with population, GDP and other independent variables. Regarding variable costs, Paravantis and Prevedouros [61] found both gasoline price and inflation to bear a significant effect in their autoregressive railway passenger models, possibly reflecting the fact that cheaper gasoline prices make traveling by car more affordable while inflation tends to impact motoring costs such as maintenance, insurance and toll fees; to this end, unemployment may also be a variable of interest.

Turning to non economic variables, vehicle occupancy (i.e. the vehicle loading factor) should be associated with car ownership. Car pooling is oftentimes encouraged (although not in Greece) with measures such as entry into fast moving lanes; car pooling may also indicate a societal change to a more environmentally friendly position possibly associated with more usage of mass transport. We decided to investigate the effect of this important parameter including recent original estimates of vehicle occupancy values for the case of Greece [62]. Transportation infrastructure may be measured by total length of roads and road density, both of which should encourage an individual to own and operate a car.

Road density is a measure of geographical coverage and accessibility to the network and should encourage car ownership [55] but is largely determined by geography and morphology and it is rather difficult to measure effectively in countries such as Greece with great inhomogeneity and a large number of islands. It is worth noting that while road infrastructure in Greece remained practically unchanged since the 1950s, numerous works have been carried out since the late 1990s funded by the EU and in anticipation of the 2004 Athens Olympics; with the exception of a few notable cases (such as the Attiki Odos tollway which commenced operation in 2002) most of these projects constituted improvement of existing rather than construction of new roads. Since both road length and road density fail to capture such improvements in existing infrastructure, lane length and density may be more appropriate metrics that could be utilized in future studies as long as a sufficient quantity of annual data since approximately 2000 become available.

In conclusion, we propose the following car ownership model (with expected signs preceding variable names):

$$\mathrm{CARS100} = f\big(+\mathrm{PCTADULT},\ +\mathrm{GDPPC},\ -\mathrm{INFL},\ -\mathrm{UNEMPL},\ -\mathrm{CARPRIC},\ -\mathrm{GAS},\\ -\mathrm{CAROCC},\ -\mathrm{BUSKM},\ -\mathrm{RAILPAS}\big).$$

Variable names are explained in Table 1.

4.2. Buses

Developing a theoretical model specification for the bus fleet is a more challenging task due to the limited amount of relevant literature. Buses are not purchased by individual consumers but either by (a) government agencies and municipal authorities in the business of mass transport or (b) private

Table 1
Variables (GRD: Greek drachmas)

Name	Description	Measurement
AR1	Autoregressive term (in GLS models)	
BUS2POP	Number of total buses per 100,000 people	
BUSES	Total number of buses	Thousand
BUSKM	Annual vehicle kilometres of a single mass transit bus	Thousand
CAROCC	Private car occupancy rate (i.e. average number of car passengers)	
CARPRICE	Average car price index (100 in 1999)	
CARS100	Number of private cars per 100 persons	
DUMMY95	Dummy variable (0 before 1995; 1 otherwise)	
GAS	Gasoline price	(GRD)
GDPPC	Gross Domestic Product per capita (1970 prices)	Thousand GRD
GDPPC95	Dummy Gross Domestic Product per capita in 1970 prices (0 before 1995; GDPPC otherwise)	Thousand GRD
INFL	Annual mid-year inflation	%
PCTADULT	Population above 17 years of age	%
PCTSENIOR	Population above 65 years of age	%
POP	Population	Million
RAILPAS	Annual rail passengers	Million
UNEMPL	Unemployment	%

enterprises usually in the field of transport or tourism (referred to as special buses by the Greek Bureau of Statistics, referred to as ESYE). More often than not, purchasing decisions of government agencies and municipal authorities are not made in response to changes in travel demand or other market realities that affect consumer behavior. In fact, in the case of many EU countries such as Greece, the availability of European funds is the most important factor in determining the timing and extent of fleet renovation.

Mass transit buses include urban and interurban vehicles (referred to as KTEL in Greece) that provide rural and intercity transportation. In many EU countries including Greece, urban buses are owned and operated by either the state or municipal authorities and the size of their fleet changes when political will and EU subsidies are in place. In Greece, interurban buses are former state monopolies (one per city) currently owned by share-holding entrepreneurs (bus owners) who employ drivers and other supporting personnel. An interesting study of the City of Ioannina KTEL, one of the few in the literature, showed a 50% profit margin on ticket sales despite the fact that prevailing worker rights prevented KTEL management from utilizing personnel rationally [63], a situation typical of most KTEL operators. The study also confirmed that new buses are mostly bought as EU subsidies become occasionally available.

In the context of this research, it was decided not to look into the different components of the bus fleet but instead model the total number of buses which we feel should provide more than enough accuracy for forecasting. To eliminate collinearity among total number of buses and population, the number of buses per 100,000 people was used as the dependent variable (BUS2POP, shown in Table 1). GDP per capita is expected to be negatively correlated with the number of buses since as income rises, people prefer cars to buses (especially so since Greece is characterized by one of the highest bus use percentages in the EU). Inflation and unemployment are expected to be positively associated with buses since when economic conditions worsen, people turn to cheaper options such as bus transportation. Finally, car occupancy should be negatively correlated to bus use and therefore number of buses.

As in the case of the car ownership model, fuel price (diesel) and the drachma equivalence rate (meaningful only until 2002 when Greece joined the monetary union) were not employed due to strong collinearity among themselves and the total number of buses. Also, we did not use the number of passenger cars per 100 people as an independent variable in the bus models because we would like to avoid forecasting one of the two dependent variables of interest via the other (in addition, CARS100 is very collinear with both PCTADULT and GDPPC).

In conclusion, we propose the following bus fleet model (expected signs indicated):

$$\begin{aligned}\mathrm{BUS2POP} = f\big(&+\mathrm{PCTADULT}\ \text{or} +\mathrm{PCTSENIOR},\ -\mathrm{GDPPC},\ +\mathrm{INFL},\ +\mathrm{UNEMPL},\\ &-\mathrm{CAROCC}\big)\end{aligned}$$

with variable names shown in Table 1.

5. Data description

Since data collected concerned Greece, it is appropriate that we present some general information of interest. The burden sharing arrangement for 6 greenhouse gas emissions from EU member countries was finalized in June 1998 at the Environment Council and set the upper limit for Greece at +25% compared to 1990 emission levels. CO_2 emissions constitute the majority (81%) of GHG emissions of

Greece and the transport sector accounts for 21% of total CO_2 emissions [64]. Transport CO_2 emissions and their increase are primarily attributed to road transport since emissions from railways and air transport are much smaller and remained constant during the 1990s.

The following socioeconomic and other data required for the estimation of the proposed model formulations were assembled for the interval 1970 to 2002: census population data from the National Statistical Bureau of Greece (ESYE); United Nations (UN) population data and projections for a medium growth scenario; various macroeconomic data, including GDP, inflation, unemployment gasoline price and a vehicle price index; vehicle fleet information including private cars and various types of urban, suburban and other public or private buses; car occupancy estimates [62]; bus vehicle kilometers and railway passengers. Variables that were used in our analysis along with their unit of measurement are shown in Table 1. Although other researchers have occasionally used historical data series that do not extend to the present day (e.g. in their 2000 work [65], Schafer and Victor employ historical data that extend up to 1990), since we were dealing with national data, it was easier to obtain annual time series data almost up to the time of writing (2002).

A few comments on historical patterns for variables of interest are now in order. The population of Greece was obtained from either ESYE Censuses (1971, 1981, 1991 and 2001) or 5-year UN data [66,67]. A discrepancy between ESYE and UN data in the mid 1990s was caused by the 2001 Census that rendered a rather high population figure (attributed to a large influx of immigrant workers mainly from Albania and other Balkan and Eastern European countries); in view of this, ESYE has recently provided updated population estimates since 1995 although even these corrected figures exhibit a rather abrupt jump in 1995. In this work we decided to use UN population figures smoothed by a Gaussian kernel weighted 3rd-degree polynomial regression.

GDP per capita (in constant 1970 prices) exhibited a slope increase around 1995. Looking at alternate income measures, GDP was better correlated to private cars than Domestic Demand. Annual mid-year inflation was very low in the beginning of the 1970s but rose significantly and fell again within the decade; it rose again especially during the early 1980s and has been falling steadily in the 1990s, exhibiting a very mild bump since 1999. Unemployment reached its lowest in the 1970s and rose significantly in the early 1980s with a slight decline in the latter part of the decade; it kept increasing at a milder slope in the 1990s and, according to ESYE, it has been declining since 1999. Since official figures for both inflation and unemployment especially after 2000 remain the subject of hot political debate in Greece, we complemented ESYE numbers with data from the Bank of Greece and the Organization for Economic Coordination and Development (confirming some discrepancies).

Gasoline price (in constant 1970 prices) arose during the gas crises of the 1970s and had been falling ever since (until the significant surge in prices during 2005). Unfortunately, there was a good amount of difficulty in obtaining reliable up-to-the-minute gas price data in Greece, so official data was available only until 1998. Regarding the impact of the two oil shocks of the 1970s (1973 and 1979), Scholl, Schipper and Kiang [12] found that the growth of both total and per capita emissions was markedly slower after the first oil shock of 1973 and, utilizing data extending back to 1960 or 1965, they concluded that the oil shocks exerted a dramatic break in the energy consumption trend, reducing both travel demand and the energy intensity of travel. On the other hand, in his classic work, Grübler [6] observed that demand grew in both industrialized and developing countries even during periods of oil price shocks such as the ones in the 1970s. We too feel that demand is likely to continue to increase at least in the immediate future despite the 2005 rally in oil prices.

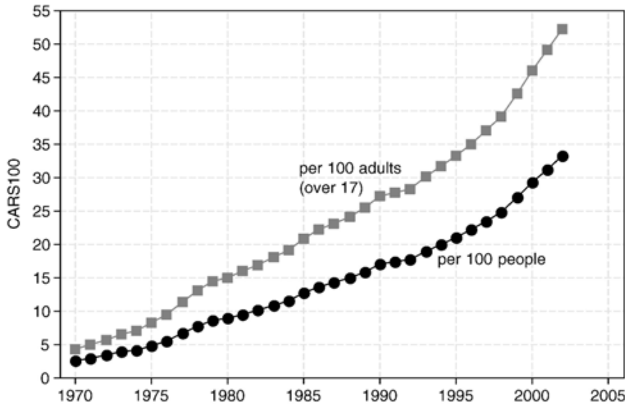

Fig. 1. Passenger cars per 100 persons (total and aged over 17).

We conclude the discussion of economic variables with a look at the deflated index of car prices showing that, in constant prices, both cars and gasoline are now cheaper than they were in 1970, a fact that constitutes a strong purchasing incentive.

Turning our attention to vehicles, Fig. 1 shows the upwards trend of passenger cars per 100 people (total as well as adults aged 17 to 65). Car occupancy rate was estimated by Danos [62]. Although car occupancy rose significantly in the first part of the 1970s (possibly in response to the energy crises), it has been on the decrease since. Referring to data from 1992 national surveys of OECD countries, Scholl, Schipper and Kiang [12] report even lower values for the average passenger car occupancy (ranging from 1.5 to 1.8). It is noted that, contrary to other parts of the world, there exist absolutely no car pooling incentives in Greece.

The number of total buses is shown in Fig. 2 (the 1981 value has been missing from the official register and was linearly interpolated) to exhibit a rather steady upwards trend which is caused by a steady increase of the number of special buses and a rather constant number of mass transit buses (not shown separately). Interestingly, annual vehicle kilometers traveled by a single bus exhibited a peak in

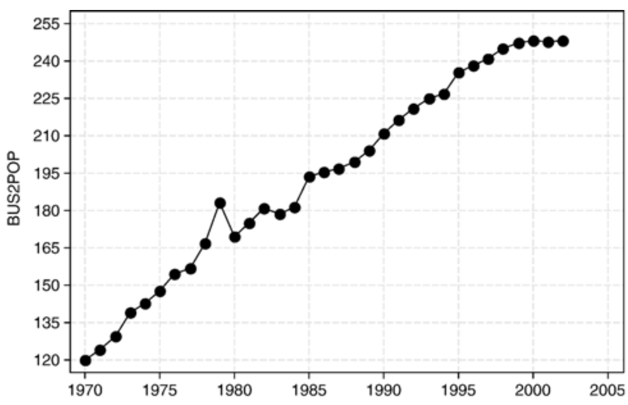

Fig. 2. Number of buses per 100,000 people.

the 1970s and a steady decline since then with the exception of 1992 to 1994 (a brief period of privatization that was later reversed).

Having completed the description of our data, we now proceed with the estimation of our models.

6. Model estimation

A few words on methods are now in order. As Kennedy aptly points out [68], in the recent past econometricians more or less ignored the effects of nonstationarity in variables involved in time series regression; this has certainly been the case with most car ownership studies (including many referenced in this work). Yet, advances in unit root research in the last 20 years or so indicate that nonstationarity must be accounted for, not by merely resorting to a more appropriate estimation method (such as GLS) but by rethinking model specification. To avoid nonsense results from spurious regression, trend stationary variables must be detrended and difference stationary (i.e. integrated) variables must be differenced before entering a regression equation either as response or predictors.

In our work, we went to great lengths to ensure that the fit of our regression models was not spurious. On one hand we decided to forgo using formal unit root tests because with a pretty small sample size (such as the one in our case with 32 data points), it is fairly difficult to reject the hypothesis of a unit root (pointed out in various sources such as [69]). On the other hand, since some of the time series data involved in both car and bus cases were probably nonstationary, we examined a number of alternative formulations in order to detect any seemingly good fit that was the result of spurious regression. We were content that there were no cases where a candidate model gave a very high R^2 combined with a very low Durbin Watson statistic (an almost sure sign of spurious regression). In fact, we only accepted alternative models that produced residuals with correlograms that appeared to originate from white noise; as a more formal check, we also carried out confirmatory analysis using both Dickey–Fuller and KPSS tests to ensure that residuals were stationary. A more detailed analysis with detrended or differenced variables would require a larger data set, possibly with monthly data.

We now proceed to estimate our proposed model formulations, first for private cars and then for buses.

6.1. Passenger car ownership model

Pearson correlation coefficients among the dependent and each independent variable are now discussed. CARS100, the dependent variable, is significantly correlated with all candidate independent variables except RAILPAS which will not be used in our modeling attempts. The correlation coefficients (R) of PCTADULT and GDPPC are over 0.9, showing extremely strong positive association with CARS100 as expected. The log of GDPPC was also tried but its association with CARS100 was weaker. Surprisingly, the correlation coefficient of UNEMPL (0.89), also shows an extremely strong positive association with CARS100, contrary to theoretical expectations. It is quite evident that this is spurious association due to similar increases of both series over time, therefore we will not use UNEMPL in our modeling attempts. The correlation coefficients of CAROCC (−0.881), BUKM (−0.828) and CARPRIC (−0.77) all show very strong negative association with CARS100, as per our expectations.

Finally, GAS (with a correlation coefficient of −0.578) and INFL (−0.429) are both negatively associated with CARS100, as expected. It is worth noting that lagged values of the GAS variable were also tested (in order to incorporate dynamic effects) but did not perform as well.

In order to anticipate multicollinearity problems, we also look at the correlation coefficients among independent variables (some of which may signify spurious association among time series). PCTADULT (our most attractive predictor) is very strongly correlated with both GDPPC (0.907) and UNEMPL (0.909); it is also strongly correlated with CARPRIC (−0.789), CAROCC (−0.85) and BUSKM (−0.797); on the other hand, its correlation to GAS and INFL while statistically significant is not very high and will not create a problem. GDPPC is strongly correlated to CARPRIC (−0.764), UNEMPL (0.744), CAROCC (−0.847, value most likely to create problems) and BUSKM (−0.745). Of the remaining pairs, CARPRIC is strongly correlated only to INFL (0.792), UNEMPL is strongly correlated to both CAROCC (−0.831) and BUSKM (−0.871) while CAROCC is strongly correlated to BUSKM (0.863). Although multicollinearity does not affect the ability of a model to predict (p.288, [70]), we will use these observations along with Variance Inflation Factors (VIFs) to diagnose significant multicollinearity problems as we develop our model.

Alternative car ownership multiple regression models are shown in Table 2. Model M1 is:

$$\mathrm{CARS100} = -110.684 + 1.759\ \mathrm{PCTADULT} + 0.144\ \mathrm{GDPPC} - 0.203\ \mathrm{BUSKM} - 0.269\ \mathrm{CAROCC}$$

$$R^2 = 0.995, D = 0.820$$

where all coefficients are statistically significant except that of CAROCC ($t=-0.56$). VIF values are interpreted according to the following rule of thumb [71]: below 5 indicate no significant multicollinearity problem, 5 to 10 are worrisome while above 10 indicate a significant multicollinearity problem and a need to seek a better model or an alternative estimation method (such as ridge regression). In the case of M1, VIFs may be between 4.2 and 6.6 (indicating a moderate multicollinearity problem) but three of the four coefficients (PCTADULT, GDPPC and BUSKM) are highly significant therefore there is no need to resort to a better model on account of multicollinearity. On the other hand, the Durbin–Watson statistic (DW) equals 0.82 which shows a statistically significant positive first order autocorrelation ($D_L=1.090$, $D_U=1.825$); a Lagrange Multiplier (LM) test (not shown in Table 2) also rejects the null hypothesis (of no statistically significant autocorrelation up to order one) at the 5% level ($p=0.003$).

Although pure autocorrelation may be expected in monthly or quarterly data, it is less likely in annual data [71] where any autocorrelation present is more likely impure i.e. a sign of errors in specification rather than a violation of technical assumptions [72]. Nevertheless, we attempt to reestimate model M1 with Generalized Least Squares (GLS) confirming that the Cochrane–Orcutt iterative procedure and a Hildreth–Lu search both converge to the same autocorrelation coefficient (rho, 0.912). The resulting model M2 indicates a similar fit (R^2-adjusted slightly improved from 0.994 to 0.997) where, as expected, only the coefficient of the autocorrelation term (AR1) and PCTADULT are now significant; the Durbin–Watson statistic remains low (0.716), indicating either a more complex correlation among residuals or (more likely since our data are annual) impure autocorrelation.

Table 2
Alternative car ownership (CARS100) multiple regression models

		Intercept	AR1	PCTADULT	DUMMY95	GDPPC	GDPPC95	BUSKM	CAROCC	s	R^2 (R^2 adj)	DW
M1	a_i	−110.684		1.759		0.144		−0.203	−0.269	0.5673	0.995	0.820
(OLS)	t			23.57		4.56		−3.44	−0.56		(0.994)	
	(p)			(0.000)		(0.000)		(0.002)	(0.582)			
n=31	VIF			5.8		5.5		4.2	6.6			
M2	a_i	−140.728	0.913	2.112		0.0505		−0.0582	−0.82	0.4229	0.997	0.716
(GLS)	t		6.115	7.107		1.433		−0.978	−1.395		(0.997)	
	(p)		(0.000)	(0.000)		(0.165)		(0.338)	(0.176)			
n=30	VIF			5.8		5.5		4.2	6.6			
M3	a_i	−101.187		1.696	−22.44	0.103	0.342	−0.224	−0.678	0.3422	0.998	1.694
(OLS)	t			31.49	−6.52	5.15	6.67	−6.26	−2.21		(0.998)	
	(p)			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.037)			
n=31	VIF			8.3	424.7	6.0	433.9	4.2	7.4			

We notice that both M1 and M2 tend to underpredict actual CARS100 values at the end of the time series, thus we decide to seek an improved model formulation with residuals that will not suffer by autocorrelation (making thus the need for GLS obsolete). Running a piecewise linear regression gave an optimum inflection point between years 1995 and 1996 (confirming what was visually evident in Fig. 1 and corresponding to the apparent slope change of per capita GDP). This apparent change in the overall trend explains why M1 and M2 underpredicted car ownership in recent years. Interestingly, it appears consistent with a state-sponsored vehicle retirement program that was in effect for a large part of the 1990s, allowing owners of older passenger vehicles to retire older non-catalytic vehicles for a rebate; it is also consistent with the start of a boom of the Greek Stock Market that started around 1996, lasted until the start of the 2000s and turned many stock holders into millionaires overnight. We suggest that money earned from the Stock Market was channeled into automobiles (and possibly other luxury goods), was a shock event that effectively shifted the demand curve that was in effect until then.

In order to capture the effect of this shock event, we decide to introduce into our model a slope dummy for the independent variable GDPPC (that represents purchasing power) that should include both a dummy intercept (DUMMY95) and a dummy slope term (GDPPC95) both of which are set to zero prior 1996 (as explained in various standard sources such as [71]). The resulting model M3 (Table 2) appears to be superior to both previous models: all variable coefficients bear the expected sign and are statistically significant, the standard error of the regression line is smaller ($s=0.3422$) and the R^2-adjusted (0.998) is higher. Regarding autocorrelation, although the Durbin–Watson value is larger than before ($D=1.694$), it now signifies an inconclusive test ($D_L=0.950$, $D_U=2.018$); on the other hand, an LM test does not reject the hypothesis of no autocorrelation up to order one ($p=0.096$). All in all, we are content that the issue of serial correlation has been accounted for by the improved model specification. Regarding multicollinearity, the fact that we now get extremely high VIF values is clearly an artifact due to the introduction of DUMMY95 and GDPPC95 that are both zero prior to 1996 (VIFs do not work well in the case of binary data). Leverage plots for these two independent variables (not shown) indicate that collinearity is not a problem and since all regression coefficients are significant ($p=0.037$ in all cases), we decide that the model is valid. We also note that the coefficients of independent variables in models M3 and M1 have not changed a lot, with the exception of CAROCC that became -0.687 (from -0.269) and is now statistically significant.

In conclusion, model M3 is our best car ownership model and may be written as follows:

$$
\begin{aligned}
<1995: \text{CARS100} = & -101.187 + 1.696\ \text{PCTADULT} + 0.103\ \text{GDPPC} - 0.224\ \text{BUSKM} \\
& - 0.678\ \text{CAROCC} \\
\\
\geq 1996: \text{CARS100} = & -123.627 + 1.696\ \text{PCTADULT} + 0.445\ \text{GDPPC} - 0.224\ \text{BUSKM} \\
& - 0.678\ \text{CAROCC} \\
R^2 = 0.998, D = 1.694.
\end{aligned}
$$

The fit of model M3 to historical car ownership data (along with predictions discussed below) is shown in Fig. 3.

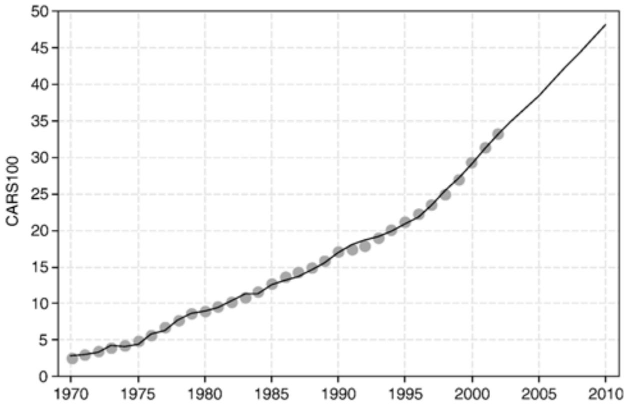

Fig. 3. Car ownership forecasts.

6.2. Bus fleet model

It is reminded that the dependent variable (BUS2POP) is defined as the number of buses per 100,000 people while the effect of population is represented in two alternative ways: PCTADULT (i.e. above 17 years of age) and PCTSENIOR (i.e. above 65 years of age) which may be a more attractive variable for buses since senior citizens are traditionally captive riders of mass media transport means.

The correlation of BUS2POP with all independent variables is statistically very significant (bigger or equal to 0.9 or lower than −0.9) in all cases except INFL. As expected, BUS2POP is strongly correlated with both PCTADULT and PCTSENIOR (R equal to 0.968 and 0.937 respectively). BUS2POP is also highly correlated with GDPPC and UNEMPL (R^2 equal to 0.925 and 0.9 respectively). CAROCC is the only predictor that is negatively correlated to BUS2POP ($R^2 = -0.91$) as per our prior expectations.

Looking for possible multicollinearity problems, we now turn our attention to association among predictors. PCTADULT and PCTSENIOR are positively correlated with an R of 0.978 but we did not intend to use both of them in the same model. Although, both happen to be positively associated with GDPPC, the correlation of PCTSENIOR is higher than that of PCTADULT (0.944 compared to 0.907). Regarding the other independent variables, both PCTADULT and PCTSENIOR are strongly associated with both UNEMPL and CAROCC. GDPPC is strongly associated with CAROCC ($R = -0.847$) and somewhat less associated to UNEMPL ($R = 0.742$). Finally, UNEMPL is strongly associated to CAROCC ($R = -831$). INFL, as in the car ownership model, is not strongly correlated with any other variables.

Our best multiple regression bus fleet models are shown in Table 3. PCTADULT and PCTSENIOR were tested as alternative ways of expressing the influence of population and we found that PCTADULT performed better in combination with INFL while PCTSENIOR with UNEMPL (albeit with some collinearity problems) while, INFL was found to be a better predictor than UNEMPL. We only show model M4, the best of these initial estimation efforts, which has an inconclusive Durbin Watson statistic ($D = 1.486$ where $D_L = 1.090$ and $D_U = 1.825$) and an LM statistic based on which we could not reject the null hypothesis of no autocorrelation ($p = 0.072$). For illustration, we mention that substituting PCTSENIOR for PCTADULT produced an rather inferior model (not shown) with clearly correlated residuals (graph not shown), and both Durbin Watson ($D = 0.468$) and LM statistics ($p = 0.000$) indicating significant autocorrelation.

Table 3
Alternative bus fleet (BUS2POP) multiple regression models

		Intercept	AR1	PCTADULT	PCTSENIOR	GDPPC	DUMMY95	GDPPC95	INFL	UNEMPL	CAROCC	s	R^2 (R^2 adj)	DW
M4	a_i	−466.95		8.335		0.914			0.699		−11.309	4.2917	0.989	1.486
(OLS)	t			12.53		3.68			5.21		−3.72		(0.988)	
	(p)			(0.000)		(0.001)			(0.000)		(0.001)			
N=31	VIF			8.0		5.9			1.5		4.6			
M5	a_i	−509.31		8.54		1.328	111.1	−1.768	0.471		−8.098	3.5191	0.993	1.921
(OLS)	t			14.90		5.94	3.06	−3.25	3.65		−3.04		(0.992)	
	(p)			(0.000)		(0.000)	(0.005)	(0.003)	(0.001)		(0.006)			
N=31	VIF			8.9		7.6	445.4	464	2.1		5.3			
M6	a_i	−77.17			12.056	1.758	184.26	−3.031		2.852	−4.974	5.4978	0.984	1.177
(OLS)	t				3.99	4.08	3.32	−3.63		3.91	−1.10		(0.980)	
	(p)				(0.001)	(0.000)	(0.003)	(0.001)		(0.001)	(0.283)			
N=31	VIF				26.3	10.9	427.3	446.2		6.0	6.2			
M7	a_i	−14.528	0.537		12.752	0.9	147.716	−2.395		2.061	−12.204	4.9276	0.987	2.007
(GLS)	t				2.96	1.63	1.90	−1.94		1.92	−1.73		(0.982)	
	(p)				(0.007)	(0.117)	(0.070)	(0.065)		(0.068)	(0.097)			
N=30	VIF				26.3	10.9	426.7	445.1		6.1	6.2			

Introducing the slope dummy used in the car ownership model in order to account for the effect of the car retirement and stock marker boom shock on the size of the bus fleet, we obtained Model M5 that appears to be significantly better than model M4 ($s=3.5191$ and $R^2=0.993$), has a borderline inconclusive Durbin Watson test ($D=1.921$ with $D_L=0.950$, $D_U=2.018$) but an LM statistic clearly not rejecting the null hypothesis on no autocorrelation ($p=0.401$). A similar model with PCTSENIOR, M6, presented an inferior fit ($s=5.4978$ and $R^2=0.984$), an inconclusive Durbin Watson ($D=1.177$ with same D_L and D_U) and an LM ($p=0.031$) statistic rejecting the hypothesis of no autocorrelation. As a last effort, we reestimated M6 with GLS (both Cochrane–Orcutt and Hildreth–Lu converging to a rho equal to 0.536) and obtained model M7 which is slightly better than M6 but inferior to M5. Regarding multicollinearity, as in car ownership, we note that high VIF values are caused by the inclusion of dummy slope variables (DUMMY95 and GDPPC95) and do not indicate an unacceptably high multicollinearity effect since regression coefficients are highly significant.

All in all, we conclude that M5 is our best bus fleet model and may be written as follows:

$$\begin{aligned} <1995: \mathrm{BUS2POP} = &-509.31 + 8.54\ \mathrm{PCTADULT} + 1.328\ \mathrm{GDPPC} + 0.471\ \mathrm{INFL} \\ &- 8.098\ \mathrm{CAROCC} \\ \geq 1996: \mathrm{BUS2POP} = &-398.21 + 8.54\ \mathrm{PCTADULT} - 0.44\ \mathrm{GDPPC} + 0.471\ \mathrm{INFL} \\ &- 8.098\ \mathrm{CAROCC} \\ R^2 = 0.993, D = 1.921. \end{aligned}$$

It is interesting to note that the slope of GDPPC is positive prior to 1996 but becomes negative after 1996, indicating that BUS2POP resembles an inferior good after 1996.

The fit of model M5 to historical data (along with predictions discussed below) is shown in Fig. 4.

7. Forecasting energy consumption and CO_2 emissions

Having selected our best car ownership and bus fleet models, we must now predict the values of independent variables included in these models up to the year 2010 (our preferred forecast

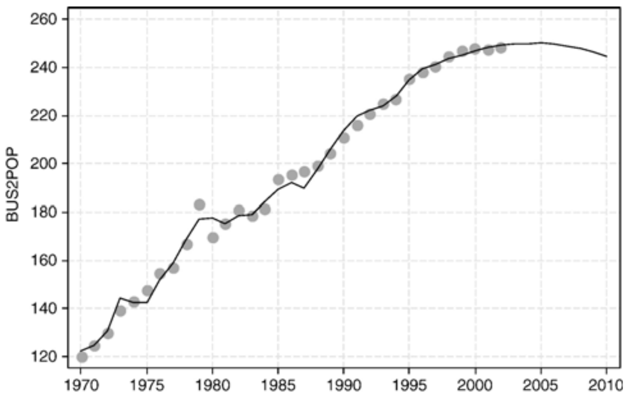

Fig. 4. Bus per 100,000 people forecasts.

horizon) so that we may then use the models to generate forecasts for the number of cars and the bus fleet.

7.1. Forecasting independent variables

Starting with predictors of the car ownership model (M3), in the case of PCTADULT, we use official UN projections resulting from the medium variant population growth scenario. For GDPPC, we employ the OECD scenario that predicts a 3.2% growth to the year 2005 and a 3.6% growth thereafter.

In the case of variables for which there exist no reliable third party forecasts, such as BUSKM, we decide to use an atheoretical approach such as ARIMA [73] where the model selection procedure involves differencing to obtain stationarity and using correlograms (i.e. autocorrelation and partial correlation plots) to select the most parsimonious model specification for which residuals appear to be pure noise. In the case of BUSKM at first we exclude the privatization years (that were quite atypical compared to the rest of the series), then produce a stationary series by taking first differences and finally we select an ARIMA(1,1,0) model. The resulting projections forecast a further decline in vehicle kilometers of a single bus which, in our opinion, is a reasonable prediction.

We use the same approach with CAROCC and select an ARIMA(0,1,1) model that predicts a further decline in car occupancy, a result we also feel comfortable with. It is worth noting that, in forecasting CAROCC, we tried excluding years corresponding to the energy crises of the 1970s but this did not make a difference.

Inflation is the only remaining predictors of the bus fleet model (M5), not included in the car ownership model. In the knowledge that official state forecasts for inflation are affected by political expediency and carried out somewhat precariously, we decided to develop our own forecast with an ARIMA(1,1,1) model. Our forecasts predicts that inflation will, more or less, remain constant until 2010.

7.2. Forecasting dependent variables

We now substitute the estimated forecasts of the independent variables into the car ownership as well as the bus fleet models and calculate the forecasts presented in Figs. 3 and 4 respectively. Fig. 3 confirms an impressively good fit to historical data and predicts that car ownership will almost hit 50 cars per 100 people in 2010. On the other hand, Fig. 4 shows a relatively good fit to historical data with a peak around 2005 and a decline to just over 240 buses per 100,000 people in 2010.

Let us now consider our findings in view of relevant literature. In his classic exposition [6], Grübler suggests that the technology cluster of which the passenger car was a central feature may be approaching limits similar to those reached in the 1920s and the 1930s by the technology cluster epitomized by the railways. Indeed, growth in car mobility appears to have slowed down since the early 1970s indicating possible saturation, while, on the other hand, long-distance means such as aircraft (worldwide) or the TGV fast trains (in France) grow spectacularly at the expense of traditional railways. In addition, there has been much speculation on the impacts of the advent of the information society (also referred to as the digital economy) on motorization, e.g. video conferencing or telecommuting may reduce the need to physically travel to work. However, as Grübler remarks, since both the telegraph and the telephone did not affect the steady exponential growth of motorized mobility at their time, it is in fact, reasonable to expect that transport and communication technologies will grow in a complementary fashion at least for quite some time. Our modeling work shows that car ownership in Greece (and other lower-income countries that resemble Greece, in EU and elsewhere) may yet exhibit dramatic increases over the next few years, potentially at the expense of mass transport media such as buses.

In a more quantitative approach, Dargay and Gately [60] estimated a simple aggregate car ownership model that represented the relationship between car ownership and per capita income as a Gompertz function on a sample of 26 countries with data spanning the period from 1973 to 1992. Their model was nonlinear and was estimated with maximum likelihood methods. To simplify estimation they assumed a common saturation level for all countries, estimated at 69 automobiles per 100 people, despite the fact that automobile cities such as Los Angeles or Dallas reached 140 cars per 100 inhabitants in the 1980s [6]. In the case of Greece they assumed an annual car usage of 15,000 km and forecasted a car ownership ratio of a mere 33 cars per 100 people for the year 2015, a number that, in fact, was exceeded in 2002. In their more detailed work quoted in a previous section [55], the previous authors employed a similar Gompertz model of car ownership with data from 26 countries over the time period 1960 to 1992 and projected, in the case of Greece, a value of 35 cars per 100 people for the year 2015. Although we agree with their conclusion that the most rapid growth in car ownership within OECD countries will occur in countries with low income but high rate of income growth (such as Greece, Portugal and Ireland), the results of our modeling work show that their projections may in fact underestimate significantly the increase in car ownership expected by 2010, underlining the ever increasing impact of private automobiles in overall increases of both fuel consumption and CO_2 emissions from road passenger transport in medium and low income countries.

7.3. Estimating fuel consumption and CO_2 emissions

From our earlier literature review, it has become evident that there exists a rather large number of literature sources with data concerning energy consumption and CO_2 emissions from passenger cars and buses. However, these data are characterized by great variability in terms of time, location, unit and value and they oftentimes provide aggregate concentrations rather than specific (i.e. per km) fuel consumption or emissions of pollutants. This is also the case with Greek data and derogates from their usefulness. To make matters worse, there has been no organized and systematic estimation of air pollutant emissions from various sources and especially from transport to date in Greece. State institutions responsible for the submission of national emission inventory data to the EU and other world organizations do not possess a detailed emission database [43]. Therefore, for the purposes of our work, we proceed based on literature values as explained below.

Zachariadis and Samaras [74] provide four official (i.e. state) specific fuel consumption estimates of interest for gasoline passenger cars in Greece: 0.111 L/km (1980), 0.101 L/km (1985), 0.101 L/km (1990) and 0.095 L/km (1995). The 1995 passenger car value is in line with the average fuel consumption of cars in Greece reported by Dargay and Gately [60], namely 0.10 L/km (1992 data). Assuming that specific fuel consumption of passenger cars in Greece through the period under examination evolved in an analogous fashion (i.e. linearly) to that of the European Union from 1985 to 1999 [34], we regress a linear trend ($R^2 = 0.853$) to these four data points and obtain fits that commence at 0.118 L/km in 1970 and end down to 0.081 L/km in 2010. Similarly, four specific fuel consumption estimates of interest are provided for heavy-duty diesel vehicles (buses, coaches and trucks) in Greece [74]: 0.323 L/km (1980), 0.343 L/km (1985), 0.314 L/km (1990) and 0.323 L/km (1995). We proceed as in the case of passenger cars and obtain an almost horizontal linear trend that provides fits from 0.336 L/km in 1970 and down to 0.313 L/km in 2010 (the fit is much worse this time; $R^2=0.093$). We feel that the steeper downwards trend in the case of passenger cars correctly reflects more significant advances in fuel economy compared to buses and coaches.

In order to estimate total CO_2 emissions, we must utilize estimates of annual mileage for passenger cars and buses. Official estimates [74] provide just three data points for annual mileage: 14,955 km (1985), 14,677 km (1990) and 14,468 km (1995). Interestingly, these three data points indicate a downward trend for the population average: regressing a line renders a 15,674 km fit for 1970, trending down to 13,726 km in 2010 ($R^2=0.993$). This downwards trend of annual mileage per vehicle correctly reflects the increase in the passenger car fleet while recent values from these estimates exceed only slightly the value of 13,000 km provided by another study [17]. The situation is a bit more complicated in the cases of buses: official estimates [74] again refer to 1985 (46,828 km), 1990 (43,584 km) and 1995 (42,317 L/km) which render a downwards linear fit ($R^2=0.940$) ranging from 53,265 km (in 1970) to 35,221 km (in 2010). Although these values are well over the 16,904 km estimate for buses and coaches provided by another study [17] we regard them as more accurate and feel content with the downwards trend that reflects the increase in the total number of buses and coaches.

According to the United Nations Framework Convention on Climate Change [75], the CO_2 emission factor from road transport for Greece is 68.61 t/tJ for gasoline and 73.80 t/tJ for diesel (1998 data). Since the energy content of gasoline is 35.97 MJ/L and that of diesel is 37.71 MJ/L [76], CO_2 emissions may be calculated at 234.45 g/km for passenger cars and 898.91 g/km for buses. These numbers compare well with corresponding data for other regions and countries reported in the literature. For example, average fuel consumption for gasoline cars is reported as 0.10 L/km for Europe [49], 0.073 L/km for the Netherlands [13] and 0.084 L/km for the EU [34]; average fuel consumption for diesel buses is reported as 0.5 L/km for Europe [46]; the CO_2 emission rate for gasoline cars is reported as 164.33 g/km [16] and 250 g/km [49] for Europe, 163 g/km for France [25] and from 146 g/km (rural) to 359 g/km (urban) for Sweden [36]; finally the CO_2 emission rate for diesel buses varies from 576.98 to 662.12 g/km [16] and from 1.31 to 1.6 g/km [46] for Europe and from 551 g/km (rural) to 994 g/km (urban) for Sweden [36].

Using the previously estimated data on specific fuel consumption and CO_2 emissions in Greece and based on the forecasts of the previous section concerning the increase in the number of passenger cars and buses from 1970 to 2010, we calculate total annual fuel consumption and CO_2 emissions for passenger cars and buses. Estimated CO_2 forecasts are depicted in Fig. 5 (note the different scale of the left and right vertical axes). We notice that car emissions keep rising while bus emissions decline sharply after the year 2000. If we consider passenger car and bus CO_2 emissions as percentages of total emissions (by cars and buses), we realize that the contribution of cars rises to almost 95% as we approach the year 2010 while the contribution of buses declines to the remaining 5% (following suit of the number of buses that is projected to start declining around 2005) in line with the decline in bus travel as we move to the year 2050 projected by Schafer and Victor [65]. It is impressive that the contribution of buses was almost 32% about 35 years ago (in 1970).

A short discussion on the reliability of our projections is now in order. A measure of uncertainty in our predictions may be obtained by comparing our estimates (based on official data) to data from the MEET (Methodologies for the Estimation of Emissions from Transport) project that provides specific fuel consumption and annual vehicle kilometers for both passenger cars and buses in years 1985, 1990 and 1995 [74]. In the case of passenger cars, MEET reports specific fuel consumption as 0.107 L/km

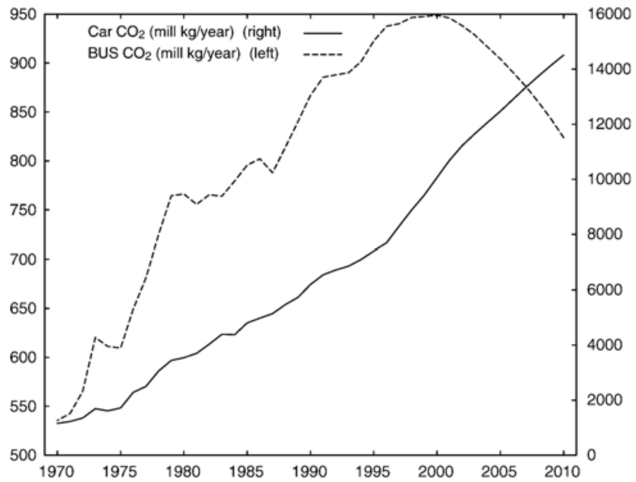

Fig. 5. Estimated CO_2 emissions from cars and buses.

(1980), 0.100 L/km (1985), 0.092 L/km (1990) and 0.088 L/km (1995), all somewhat lower than the official values utilized in our study; on the other hand, MEET reports somewhat higher annual passenger car mileage: 15438 km (1985), 14874 km (1990) and 15196 km (1995), offsetting the lower specific fuel consumption values. In the case of buses, MEET estimates somewhat lower specific fuel consumption values that also seem to decline very gently since 1970: 0.280 L/km (1980), 0.279 L/km (1985), 0.278 L/km (1990) and 0.276 L/km (1995). Yet MEET estimates much lower annual mileage values: 18,040 km (1985), 13,066 km (1990) and 10,477 km (1995). This means that the overall contribution to CO_2 emissions by buses is likely to be significantly lower than the one projected in our study, a fact that underlines the importance of passenger cars and provide a further boost to our conclusions.

Although fuel prices were not included in our models, fuel economy and its dependence on socioeconomic characteristics (such as per capita income and fuel prices) remains an important issue. In an interesting study, Espey [77] observed that overall fuel efficiency of the vehicle fleet in the USA has increased by about 50% since 1970 despite the fact that real fuel prices today are nearly the same as they were in 1970. Similar observations hold in the case of most European countries in which average fleet fuel economy improved steadily during the 1980s despite declining real fuel prices (the increase of fuel prices during the energy crises of the 1970s were followed by steadily decreasing real fuel prices through most of the 1980s). Espey modeled the role of fuel prices, income, government taxation and technological change in influencing consumer choice of fuel economy based on data derived from the USA, Japan, France, Germany, the UK, Norway, Sweden and Denmark using real gross domestic product per capita as a proxy for income. The results of his analysis imply that consumer choice of automobile fuel efficiency is not as sensitive to fuel prices and income as previously believed: while previous literature has estimated the elasticity of fuel efficiency with respect to income at about -0.20 (implying that fuel economy is reduced when income per capita increases as it usually does over time) actual figures show that while real GDP per capita in the USA increased by about 16% between 1981 and 1988, fuel economy rose (instead of falling as indicated by the negative sign of the elasticity) by about 20% during the same time period. All in all, these findings support our decision to assume that fuel consumption (expressed in liters per kilometer) in the case of Greece has exhibited a more-or-less linear downwards trend during the study time period independently of any fluctuations in income and fuel prices.

8. Conclusions and recommendations

The passenger car ownership as well as bus fleet aggregate models that were developed, allowed us to compare CO_2 emissions from these two important road transportation media and conclude that the passenger automobile will emerge as the dominant CO_2 source in road passenger transport (disregarding the contribution of taxicabs and mopeds) within the current decade (2000 to 2010) in the case of Greece. Keeping in mind the resemblance in both socioeconomic variables as well as transport characteristics that Greece bears to other EU countries in the Mediterranean and Eastern Europe, we believe that our results indicate that analogous situations may be expected in a number of EU countries.

This increasing share of automobiles in CO_2 emissions from road passenger transport, presents a formidable challenge. As Scholl, Schipper and Kiang [12] point out, reducing CO_2 emissions will involve changes in a combination of factors such as adoption of renewable or non-fossil based fuels, significant declines in energy intensity, shift to less energy intensive modes and reductions in travel. Declines in energy intensity refer to important technological improvements (such as fuel economy) that are taking place very slowly as well as increases in load factors (i.e. car occupancy). As Dargay and Gately point out [60], it is unlikely that considerable fuel economy increases will be introduced without external stimuli such as substantial fuel price increases (such as the one witnessed during the first months of 2005). Selected alternative technologies such as fuel cells and gasoline–electricity hybrid vehicle engine, have lately received quite a lot of attention for their potential in reducing CO_2 emissions in the road transport sector (see for example [78]) but they are unlikely to bear any influence on our 2010 forecasts as their move from innovation to diffusion is likely to take significantly longer [6]. On the other hand, a reduction of travel along with a shift to less energy intensive modes may, in all likelihood, only be expected if environmental costs are internalized through appropriate pricing policies [12].

In closing our work, we now turn to recommendations for further research:

– Although we focused our attention on passenger cars and buses, other road means offer passenger transport such as mopeds (short distances in good weather mostly), taxicabs (short and medium distances) and railways (medium and longer distances); in the case of Greece where 14% of its total population dwell in islands that constitute 19% of the total area of the country [79], even coastal shipping enters the picture. In this work, available railway data did not appear to exert a significant influence on either passenger cars or buses, reflecting the extremely small and ever declining market share of the Hellenic Railways Organization in passenger transport in Greece [61]. Yet, the influence of mopeds and taxicabs, small as it may be, should be further investigated.
– In this work, we chose, for simplicity, to model the total number of buses. In reality, total buses are the sum of special buses (including tourist buses) and urban/suburban buses. These two different groups of buses exhibit different trend and fluctuation characteristics, therefore developing separate aggregate models for each group may result in better predictions.
– As a final recommendation, developing regional car ownership forecasts would be of especial interest in Greece where, for instance, approximately 30% of its total population is gathered in the Athens area [80]. This would allow us to incorporate additional information such as regional road density or

even socioeconomic characteristics such as household size (that were ignored in this work carried out on a countrywide level). Such regional models would allow us to separate the contribution of the dynamics of different prefectures on the country average (captured by the models developed in this paper).

Acknowledgments

We are indebted to Professor Allin Cottrell of Wake Forest University for his valuable insight on Generalized Least Squares and Unit Root testing as well as for additions made to his superb Gretl freeware econometric package on our request. We are also grateful to Mr. Markos Tsogas, PhD candidate extraordinaire at the University of Piraeus, for his perceptive recommendations on piecewise regression. Finally, we thank Ms. Olga Papantoniou of the Statistics Division of the Bank of Greece for kindly making a large volume of time series data available to us.

References

[1] T.H. Ortmeyer, P. Pillay, Trends in transportation sector technology energy use and greenhouse gas emissions, Proc. I.E.E.E. 89 (12) (December 2001) 1837–1846.

[2] T. Zachariadis, N. Kouvaritakis, Long-term outlook of energy use and CO_2 emissions from transport in central and eastern Europe, Energy Policy 31 (8) (2003) 759–773.

[3] A. Beggs, Energy management, supply and conservation, Butterworth-Heinemann, Oxford, 2002.

[4] European Environment Agency, Energy Consumption, Version 20-08-2001, 2001, pp. 1–8.

[5] M. Walsh, "European Environment Agency Says Transport Sector Falling Short of Goals", Car Lines, Issue 2000-3, May 2000.

[6] A. Grübler, Technology and global change, Cambridge University Press, 1998.

[7] European Union (EU), Energy and Transport in Figures, Directorate-General for Energy and Transport in cooperation with Eurostat, 2004.

[8] A. Mourelatou, I. Smith, Energy and the Environment in the European Union, European Environment Agency, Environmental Issue Report No. 31, Copenhagen, 2002, pp.27–33.

[9] B. Johansson, M. Ehman, A comparison of technologies for carbon neutral passenger transport, Transp. Res., Part D Transp. Environ. 7 (2002) 175–196.

[10] European Environment Agency, "Transport Emissions and Greenhouse Gases by Mode", Indicator Factsheet, Term 2003 02 EEA 31, 2003.

[11] European Environment Agency, Emissions of Greenhouse Gases, Version 20-08-2001, 2001, pp.1–14.

[12] L. Scholl, L. Schipper, N. Kiang, CO_2 emissions from passenger transport: a comparison of international trends from 1973 to 1992, Energy Policy 24 (1) (1996) 17–30.

[13] R.M.M. Van den Brink, B. Van Wee, Why has car-fleet specific fuel consumption not shown any decrease since 1990? Quantitative analysis of Dutch passenger car-fleet specific fuel consumption, Transp. Res., Part D Transp. Environ. 6 (2001) 75–93.

[14] B. Van Wee, J.A. Annema, Transport, energy savings and CO_2 emissions reductions: technical–economic potential in European studies compared, Proceedings of the IEA International Workshop on Technologies to Reduce Greenhouse Gas Emissions, Washington D.C., 5–7 May 1999 (1999).

[15] P. Ahlvik, S. Eggleston, N. Gorißen, D. Hassel, A.J. Hickman, R. Joumard, L. Ntziachristos, R. Rijkeboer, Z. Samaras, K.H. Zierock, COPERT II – Computer Programme to Calculate Emissions from Road Transport – Methodology and Emission Factors, European Environment Agency, Technical Report No. 6, 1997.

[16] J.A. Cox, A.J. Hickman, Aggregated Emission Factors for Road and Rail Transport — MEET Project: Methodologies for Estimating Air Pollutant Emissions From Transport, Deliverable No. 23, 1998.

[17] LAT/AUTH, Methodologies for Estimating Air Pollutant Emissions from Transport. Road Traffic Composition, Aristotle University of Thessaloniki, LAT Report No:9823, Thessaloniki, 1998, pp. 71–78.

[18] R. Joumard, Methods For Estimations of Atmospheric Emissions from Transport: European Scientist Network and Scientific State-Of-The-Art, Action COST 319 Final Report.
[19] A.J. Hickman, Methodology for Calculating Transport Emissions and Energy Consumption— MEET Project: Methodologies for Estimating Air Pollutant Emissions from Transport, Deliverable No. 22, Transport Research Laboratory, 1999.
[20] L. Ntziachristos, Z. Samaras, COPERT III – Computer Programme to Calculate Emissions from Road Transport – Methodology and Emission Factors (Version 2.1), Technical Report No. 49, European Environment Agency, 2000.
[21] P. Bickel, S. Schmid, W. Krewitt, R. Friedrich, External costs of transport in ExternE, IER, Germany, 1997.
[22] S. Banfi, C. Doll, M. Maibach, W. Rothengatter, P. Schenkel, N. Sieber, J. Zuber, External costs of transport — accident, environmental and congestion costs in Western Europe, INFRAS/IWW, Zórich/Karsruhe, 2000.
[23] G. Vossiniotis, D. Assimakopoulos, The marginal environmental costs of transport in Greece, Global NEST, Int. J. 1 (2) (1999) 77–89.
[24] M. Beuthe, F. Degrandsart, J.F. Geerts, B. Jourquin, External costs of the Belgian interurban freight traffic: a network analysis of their internalisation, Transp. Res., Part D Transp. Environ. 7 (2002) 285–301.
[25] M. André, U. Hammarström, Driving speeds in Europe for pollutant emissions estimations, Transp. Res., Part D Transp. Environ. 5 (2000) 321–335.
[26] E. Eriksson, Independent driving pattern factors and their influence on fuel-use and exhaust emission factors, Transp. Res., Part D Transp. Environ. 6 (2001) 325–345.
[27] L. Schipper, D. Steiner, P. Duerr, A. Feng, S. Stroem, Energy use in passenger transport in OECD countries: changes since 1970, Transport 19 (1992) 25–42.
[28] M.E. Bouwman, H.C. Moll, Environmental analyses of land transportation systems in the Netherlands, Transp. Res., Part D Transp. Environ. 7 (2002) 331–345.
[29] European Environment Agency, Energy Efficiency and Specific CO_2 Emissions, Version 20-08-2001, 2001, pp.1–4.
[30] European Environment Agency, Specific Emissions of Air Pollutants, Version 20-08-2001, 2001, pp.1–11.
[31] C.A. Lewis, Fuel and Energy Production Emission Factors— MEET Project: Methodologies for Estimating air Pollutant Emissions from Transport, Deliverable No. 20, 1997.
[32] S. Perkins, "CO_2 Emissions from Transport", Presentation to the *Third Conference of The Parties*, UN Framework Convention on Climate Change, Kyoto, Japan, 1–10 December 1997.
[33] European Commission, EU energy and transport, office for official publications of the EU, Luxembourg, 2001.
[34] Enerdata and FhG/ISI, Energy Efficiency in the European Union 1990–2001, SAVE ODYSSEE Project on Energy Efficiency Indicators, 2003.
[35] E. Eriksson, M. Blinge, G. Lövgren, Life cycle assessment of the road transport sector, Sci. Total Environ. 189/190 (1996) 69–76.
[36] H. Johansson, M. Ek, Emissions from Transport in Sweden, Report 2003:5E, TFK, Stockholm, 2003.
[37] P. Romilly, Substitution of bus for car travel in urban Britain: an economic evaluation of bus and car exhaust emission and other costs, Transp. Res., Part D Transp. Environ. 4 (1999) 109–125.
[38] A. Andrias, I. Tibanidis, T. Zachariadis, G.Z. Samaras, Forecast of emissions from road traffic in Greece in the period 1990–2010, Technika Chronika, IV 2 (1997) 7–21 (in Greek).
[39] T. Zachariadis, G. Tsilingiridis, G.Z. Samaras, Estimation of air emissions with high spatial and temporal resolution: application in the case of road traffic emissions, Technika Chronika, IV 2 (1997) 35–48 (in Greek).
[40] P.D. Kalabokas, L.G. Viras, C.G. Reparis, Analysis of the 11-year record (1987–1997) of air pollution measurements in Athens, Greece: Part I. Primary air pollutants, Global NEST, Int. J. 1 (3) (1999) 157–167.
[41] P.D. Kalabokas, L.G. Viras, C.G. Reparis, J.K. Bartzis, Analysis of the 11-year record (1987–1997) of air pollution measurements in Athens, Greece: Part II. Petrochemical air pollutants, Global NEST, Int. J. 1 (3) (1999) 169–176.
[42] P. Simeonidis, I. Ziomas, A. Proyou, Emissions of air pollutants from the road transport sector in Greece: year to year variation and present situation, Environ. Technol. 24 (6) (2003) 719–726.
[43] P. Simeonidis, I. Ziomas, A. Proyou, Development of an emission inventory system from transport in Greece, Environ. Model. Softw. 19 (4) (2004) 413–421.
[44] A. Schafer, Carbon dioxide emissions from world passenger transport, Transp. Res. Rec. 1738 (2000) 20–29.
[45] A. Schafer, Carbon dioxide emissions from world passenger transport — reduction options, Transp. Res. Rec. 1936 (2000) 20–29.

[46] A. Rabl, Environmental benefits of natural gas for buses, Transp. Res., Part D Transp. Environ. 7 (2002) 391–405.
[47] B. Ubbels, P. Rietveld, P. Peeters, Environmental effects of a kilometer charge in road transport: an investigation for the Netherlands, Transp. Res., Part D Transp. Environ. 7 (2002) 255–264.
[48] D. Salon, D.J. Dudek, Applying greenhouse gas emissions trading to the light-duty vehicle sector, Transp. Res. Rec. 1664 (1999) 3–8.
[49] J. Albrecht, The diffusion of cleaner vehicles in CO_2 emission trading designs, Transp. Res., Part D Transp. Environ. 5 (2000) 385–401.
[50] Y. Hayashi, H. Kato, R. Teodoro, A model system for the assessment of the effects of car and fuel green taxes on CO_2 emission, Transp. Res., Part D Transp. Environ. 6 (2001) 123–139.
[51] G. Baiocchi, W. Distaso, GRETL: econometric software for the GNU generation, J. Appl. Econ. 18 (2003) 105–110.
[52] P.D. Prevedouros, P. An, Automobile ownership in Asian countries: historical trends and forecasts, ITE J. 68 (1998) 24–29.
[53] W.H.K. Lam, M.L. Tam, Reliability of territory-wide car ownership estimates in Hong Kong, J. Transp. Geogr. 10 (2002) (2002) 51–60.
[54] D. Gately, The US demand for highway travel and motor fuel, Energy J. 11 (3) (1990) 59–72.
[55] J. Dargay, D. Gately, Income's effect on car and vehicle ownership, Transp. Res., Part A, Gen. 33 (1999) 101–138.
[56] Goodbody Economic Consultants, Travel Demand, Dublin, Ireland, 2000 November.
[57] London Borough of Croydon, Transport, Croydon Environment Audit, No.7, London, 1995.
[58] K.J. Button, A.S. Fowkes, A.D. Pearman, Disaggregate and aggregate car ownership forecasting in Great Britain, Transp. Res., Part A, Gen. 14A (1980) 263–273.
[59] D. Baldwin Hess, P.M. Ong, "Traditional Neighborhoods and Auto Ownership", Working Paper #37, Working Paper Series, The Ralph and Goldy Lewis Center for Regional Policy Studies, School of Public Policy and Social Research, University of California at Los Angeles (UCLA), 2001.
[60] J. Dargay, D. Gately, Vehicle ownership to 2015: implications for energy use and emissions, Energy Policy 25 (14–15) (1997) 1121–1127.
[61] J.A. Paravantis, P.D. Prevedouros, Railroads in Greece: history, characteristics and forecasts, Transp. Res. Rec. (1742) (2001) 34–44.
[62] S. Danos, A Comparative Evaluation of Aggregate Car Ownership Models in Order to Forecast Fuel Consumption and CO2 Emissions in Passenger Transport: the Case of Greece, MSc Thesis, University of Piraeus, 2004 (in Greek).
[63] J. Paravantis, A quantitative survey of transport mobility of passengers and goods in Epirus, 15th National Conference of the Hellenic Society of Operations Research (EEEE), Tripolis, Oct. 31–Nov. 2, 2002.
[64] D.P. Lalas, D. Koutentaki, E. Georgopoulou, J. Sarafidis, S. Mirasgentis, Climate Change Emissions Inventory: National Inventory for Greenhouse and Other Gases for the Years 1990–2000, prepared by the National Observatory of Athens on behalf of the Ministry for the Environment, Physical Planning and Public Works, 2002 May 31st.
[65] A. Schafer, D.G. Victor, The future mobility of the world population, Transp. Res., Part A, Gen. 34 (2000) 171–205.
[66] United Nations, World Urbanization Prospects: The 2001 Revision, Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat (http://esa.un.org/unpp).
[67] United Nations, World Population Prospects: The 2002 Revision, Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat (http://esa.un.org/unpp).
[68] P. Kennedy, A guide to econometrics, 4th edition, The MIT Press, Cambridge, Massachusetts, 2001.
[69] J.M. Wooldridge, Introductory econometrics: a modern approach, 2nd edition, Thomson South-Western, 2003.
[70] S. Makridakis, S.C. Wheelwright, R.J. Hyndman, Forecasting: methods and applications, 3rd edition, John Wiley and Sons, 1998.
[71] A.H. Studenmund, Using econometrics, 2nd edition, Harper Collins, 1992.
[72] D.F. Hendry, G.E. Mizon, Serial correlation as a convenient simplification, not a nuisance: a comment on a study for money by the Bank of England, Econ. J. 88 (September 1978) 549–563.
[73] G.E.P. Box, G.M. Jenkins, G.C. Reinsel, Time series analysis: forecasting and control, 3rd edition, Prentice-Hall International, 1994.
[74] T. Zachariadis, Z. Samaras, Validation of road statistics through energy efficiency calculations, Energy 26 (2001) 467–491.
[75] United Nations Framework Convention on Climate Change, Synthesis and Assessment Report on the Greenhouse Gas Inventories Submitted in 2004, FCCC/WEB/SAI/2004, 2004, p. 53.

[76] I. Boustead, G.F. Hancock, Handbook for Industrial Energy Analysis, Ellis Horwood Limited and John Wiley and Sons, Chichester, 1979.
[77] M. Espey, Watching the fuel gauge: an international model of automobile fuel economy, Energy Econ. 18 (1996) 93–106.
[78] T. Kosugia, K. Tokimatsub, H. Yoshidac, Evaluating new CO_2 reduction technologies in Japan up to 2030, Technol. Forecast. Soc. Change 72 (2005) 779–797.
[79] E. Sambracos, J.A. Paravantis, C.D. Tarantilis, C.T. Kyranoudis, Dispatching of small containers via coastal freight liners: the case of the Aegean Sea, Eur. J. Oper. Res. 152 (2004) 365–381.
[80] National Statistical Service of Greece (ESYE), Greece in Figures, 2003.

John Paravantis is a Lecturer in the Department of Technology Education and Digital Systems at the University of Piraeus. He holds a Civil Engineering degree from the National Technical University of Athens as well as an M.Sc. in Transportation and a PhD in Environmental Health both from Northwestern University. In his professional career prior to joining the academia, he supervised the drafting of over 40 Environmental Impact Statements mostly of large engineering works and was a member of the project management team for the renovation of infrastructure of the Hellenic Railways Organization. In his research he employs optimization techniques and econometric models in order to investigate impacts from the use of energy in production, transport and building technologies; some of his work has been published in Energy and Buildings, the European Journal of Operations Research and the Transportation Research Record.

Dimitris Georgakellos is an Assistant Professor in the Department of Business Administration at the University of Piraeus. He received his graduate degree in Mechanical Engineering from the National Technical University of Athens and his doctoral degree in Business Administration from the University of Piraeus. He has more than 10 years of project experience in the private sector. His current research interests focus on Environmental Economics and Management, Technology and Innovation Management and Energy Management.